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A novel low implementation-cost spectrum sensing technique for cognitive radio systems

Técnica de detección espectral de bajo costo para sistemas de radios cognitivos

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Abstract

One of the greatest current challenges in telecommunications is the excessive exploitation of the radio spectrum, and the migration of new services to higher frequencies is becoming a problem since this implies a higher cost for the development of electronic equipment and the effective range of these decreases. This makes it essential that new equipment has the capacity for efficient and collaborative use and reuse of the radio spectrum. Spectral sensing is therefore of vital importance in new electronic devices, along with the possibility of local spectrum sensing, spectrum management, frequency reuse, distributed communication capabilities in the framework of cognitive radio systems, etc.
The present work proposes a variant for the cross-correlation estimator in a cyclostationary detector to be implemented in a spectral detector and its comparison with other classical estimators.

Keywords: estimator, spectral detection, cross-correlation.

Resumen

Uno de los mayores retos actuales en telecomunicaciones es la explotación excesiva del espectro radioeléctrico. La migración de nuevos servicios a frecuencias más altas se está convirtiendo en un problema, ya que implica un mayor costo para el desarrollo de equipos electrónicos y el alcance efectivo de estos disminuye, lo que provoca que sea esencial que los nuevos equipos cuenten con la capacidad de utilizar y reutilizar el espectro radioeléctrico de forma eficiente y colaborativa.
Por lo tanto, la detección espectral es de vital importancia en los nuevos dispositivos electrónicos, junto con la posibilidad de detección local de espectro, gestión del espectro, reutilización de frecuencias, capacidades de comunicación distribuida en el marco de los sistemas de radio cognitiva, etc.

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El presente trabajo propone una variante para el estimador de correlación cruzada en un detector cicloestacionario para su implementación en un detector espectral y la comparación con otros estimadores clásicos.

Palabras clave: estimador, detección espectral, correlación cruzada.

1. Introduction

The cognitive radio (CR) paradigm is a promising candidate for the solution of efficient spectrum use through the incorporation of capabilities into the equipment, such as the ability to detect and share unused spectrum and its management, among others. This, associated with the energy detection (ED) technique, is presented as a promising candidate in order to improve the efficiency of frequency spectrum assignments (Lorincz et al., 2021). This technique is highly regarded among the available spectrum sensing techniques due to its low computational complexity and implementation costs.

Energy detection is the most widely used technique since no previous knowledge of the input signal is required; however, its performance degrades at low SNR values.

Theoretical analyses show that when $SNR \ll 1$, the number of samples required to achieve a certain probability of detection and false alarm is proportional to $1/SNR^2$ asymptotically. The performance of the energy detector is very sensitive to the error in the estimated noise power (Lu et al., 2012).

This disadvantage can be circumvented by implementing the energy detection algorithm from cyclostationary detection (Mitola, 1999; Proakis & Manolakis, 2007; Zhang, 2017), which implements a correlation estimator, making it a more robust technique to noise than energy detection, but at the same time, it assumes that the signal of interest exhibits a cyclostationary characteristic, which is a typical characteristic of communication signals.

Consequently, cyclostationary detection is a natural candidate for the detection of sub-Nyquist sample spectra at low SNRs.

This paper presents the implementation and analysis of some proposed estimators, such as a candidate cross-correlation estimator, a correlation estimator based on the sample mean, a correlation estimator based on the sample median, a more robust estimator called Sample Median Covariance, and a robust estimator based on the sample median. The analysis of the estimators was carried out based on the noise; later, a performance comparison was made between them. Finally, the implementation in a hardware and software system was proposed by the author.

2. State of Art

According to Lorincz et al. (2021), an analysis of the different most commonly used detection methods compared to the energy detection method was performed, and the results are presented in Table 1.

Table 1. Comparison of methods

Parameters for Comparison with ED Method	Matched filter detection (MFD)	Cyclostationary feature detection (CFD)	Entropy detection method (END)	Waveform based detection (WBD)	Goodness of fit test detection (GFTD)	Eigenvalue based detection (EBD)
Detection accuracy at all SNRs.	*Significantly better*	*Better*	*Better*	*Significantly better*	*Somewhat better*	*Better*
Amount of prior PU information	*Significantly higher*	*Higher*	*Equal (no PU information)*	*Higher*	*Equal (no PU information)*	*Equal (no PU information)*
Sensing time	*Lower*	*Similar*	*Similar*	*Lower*	*Lower*	*Similar*
Robustness against NU	*More robust*	*Significantly more robust*	*More robust*	*More robust*	*Similar*	*More robust*
Computational complexity	*More complex*	*Significantly complex*	*More complex*	*More complex*	*Somewhat complex*	*More complex*

The table shows that the cyclostationary detection method performs better in terms of detection accuracy at all SNRs, amount of prior PU information, sensing time, and robustness in contrast with NU. Regarding computational complexity, it requires greater resources.

3. Cyclostationary Detector

The cyclostationary detector, in addition to assuming that the signal of interest exhibits a cyclostationary characteristic, detects periodic features in the received signal. Consequently, cyclostationary detection is a natural candidate for detecting sub-Nyquist sample spectra at low SNRs.

A cyclostationary signal is characterized by the fact that its mean and autocorrelation function are periodic in time. As in conventional signal analysis, processing can be performed in the time or frequency domain.

A signal is cyclostationary when any of its statistical parameters, such as mean value or autocorrelation, is a periodic function of time.

A cyclostationary process is a signal that has statistical properties that vary cyclically with time (Gardner, 1991). A cyclostationary process can be viewed as multiple interspersed stationary processes.

Cyclostationary signals exhibit a correlation between spectral components that are far apart due to spectral redundancy caused by periodicity.

These characteristics can be detected by analyzing the cyclic spectral density (CSD) function from the power spectral density, which can be seen in Equation 1.

$$PSD = R_x^{\alpha}(\tau) = \sum_{n=0}^{N-1} r[\tau] e^{-j\frac{2\pi}{N}n\alpha} \tag{1}$$

Where $R_x^{\alpha}(\tau)$ is referred to as the cyclic auto-correlation function (CAF) at the cyclic frequency α. Cyclic frequencies are usually harmonics of the fundamental frequency and are related to the symbol ratio, which is the carrier frequency.

As the PSD is a stationary stochastic process, this implies that it can be obtained from the Fourier transform of its autocorrelation $r[\tau]$, which can be seen in Equation 2.

$$r_\tau = r[\tau] = \frac{1}{N} \sum_{n=0}^{N-1} x_n[n] * x_n[n+\tau] \tag{2}$$

$r[\tau]$ is an estimator of the classical semivariogram (CSV) proposed by Matheron in 1962 (Saccomano et al., 2001).

Cyclostationary signals exhibit a correlation between spectral components that are far apart due to spectral redundancy caused by periodicity.

These characteristics can be detected by analyzing the Cyclic Spectral Density (CSD) function of the received signal, which can be seen in Equation 3.

$$SCD = S_x^{\alpha}(f) = \sum_{\tau=-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau} \tag{3}$$

Communication signals usually exhibit statistical periodicity due to modulation schemes such as carrier modulation or periodic coding (Chatfield, 1989). Therefore, such signals are better modeled as stationary cycling processes rather than stationary processes.

The cyclic spectrum of $S_x^{\alpha}(f)$ extends the traditional power spectrum to a two-dimensional map with respect to two frequency variables, angular and cyclic. The cyclic spectrum exhibits spectral peaks at certain frequency locations, the cyclic frequencies, which are determined by the signal parameters, particularly the carrier frequency and the symbol rate (Gardner, 2006). This constitutes the main advantage of cyclostationary detection.

Cyclostationary detection is also possible by employing cross-correlation of the input signal. Gadner (1994) proposes a way to obtain the $S_x^{\alpha}(f)$, which can be seen in Figure 1.

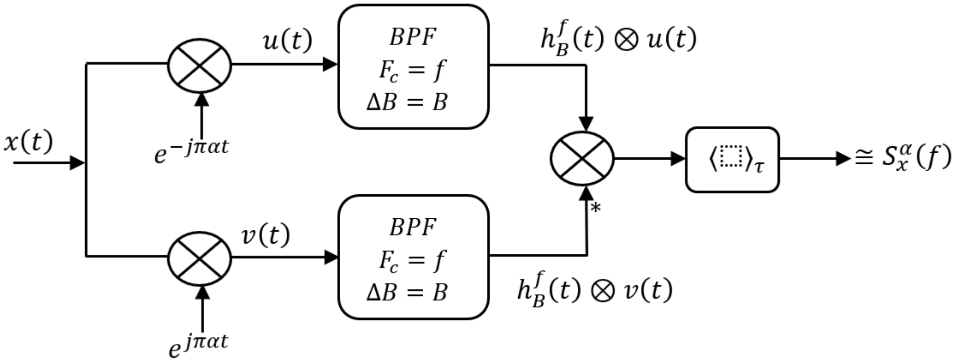

Figure 1. Block diagram

Where $h_B^f\left(t\right)$ is the impulse response, the center frequency band-pass filter f with unity gain at this frequency and bandwidth B, the symbol ⊗ denotes the convolution operation; α is the cyclic frequency.

Gardner demonstrated that the SCD function obtained by $S_x^\alpha\left(f\right)$, is the cross spectrum of the signal and a frequency-shifted version of itself, providing a second-order statistical description in the frequency domain of such signals (William & Herschel, 1993).

The calculation of $S_x^\alpha\left(f\right)$ can be summarized in Equation 4.

$$S_x^\alpha\left(f\right) \triangleq \lim_{B\to 0}\frac{1}{B}\left[h_B^f\left(t\right)\otimes u\left(t\right)\right]\left[h_B^f\left(t\right)\otimes v\left(t\right)\right] \tag{4}$$

Where u(t) and v(t) are two frequency-shifted versions of x(t), as can be seen in Equations (5) and (6).

$$u\left(t\right)=i\left(t\right)=x\left(t\right).e^{-j\pi\alpha t}=x\left(t\right).\left(\cos\left(\pi\alpha t\right)-j\sin\left(\pi\alpha t\right)\right) \tag{5}$$

$$v\left(t\right)=q\left(t\right)=x\left(t\right).e^{j\pi\alpha t}=x\left(t\right).\left(\cos\left(\pi\alpha t\right)+j\sin\left(\pi\alpha t\right)\right) \tag{6}$$

This last approximation of the $S_x^\alpha\left(f\right)$ is more suitable for cognitive radio systems, since I/Q quadrature signals allow digital demodulation of signals.

4. Proposed Estimate

There are two different approaches to the treatment of cyclostationary processes (Walpole et al., 2012). First, the probabilistic approach consists of viewing the measurements as an instance of a stochastic process. Second, the deterministic approach consists of viewing the measurements as a single time series, from which a probability distribution can be defined for some event associated with the time series. In both approaches, the process or time series is said to be cyclostationary if and only if its associated probability distributions vary periodically with time.

Based on the probabilistic approach, we can define an estimator as a statistic used to estimate an unknown parameter (Walpole et al., 2012). It is desirable that the estimator has certain properties, such as being unbiased and robust.

According to Rodríguez Jáuregui (2005), one of the most robust estimators against noise is the correlation estimator based on the mean, which can be seen in Equation (7).

$$\bar{R}_{XY} = \left(\frac{1}{N} \sum_{n=0}^{N-1} \left| Y_{n-\tau} \right| \right) . \sum_{n=0}^{N-1} \frac{\left(\left| Y_{n-\tau} \right| . \left| sgn\left(Y_{n-\tau}\right) . \left(X_{n-\tau}\right) \right| \right)}{\sum_{n=0}^{N-1} \left| Y_{n-\tau} \right|} \tag{7}$$

Taking into account that a correlation estimator based on the median is more robust in the presence of noise of an impulsive nature (Rodríguez Jáuregui, 2005), it demonstrates a better performance in relation to correlation estimators based on the mean and on the maximum likelihood principle. The expression of the correlation based on the sample median can be seen in Equation (8).

$$\tilde{R}_{XY} = \left(\frac{1}{N} \sum_{n=0}^{N-1} \left| Y_{n-\tau} \right| \right) . \tilde{\beta} \tag{8}$$

where $\tilde{\beta}$ is called the weighted median. Equation 8 is the product of the average of the absolute value of the samples Yi and the weighted sum of the samples Xi. Moreover, the weighted mean is the location parameter for the Gaussian case, and the weighted median corresponds to the location parameter for the Laplacian case.

Equation (8) may not be very robust due to the average operation involved in the correlation calculation, in the case that one of the samples Yi is an impulse. In order to achieve greater robustness to impulses, the calculation of the mean can be replaced by the sample median, obtaining a more robust estimator called the sample median covariance (Arce & Li, 2002), which can be seen in Equation (9).

$$\hat{R}_{XX} = \left(\sum_{n=0}^{N-1} \left| X_{n-\tau} \right| \right) . \sum_{n=0}^{N-1} \left(\left| X_{n-\tau} \right| . \left| sgn\left(X_n \right) . \left(X_{n-\tau} \right) \right| \right) \tag{9}$$

Applying the same analysis in the case of autocorrelation, the sample median self-consciousness is obtained, which can be observed in Equation (10).

$$\hat{R}_{XX} = \left(\sum_{n=0}^{N-1} \left| X_{n-\tau} \right| \right) . \sum_{n=0}^{N-1} \left(\left| X_{n-\tau} \right| . \left| \left(X_n \right) . \left(X_{n-\tau} \right) \right| \right) \tag{10}$$

In order to improve the performance both in sensitivity and implementation, a new cross-correlation estimator was proposed by adding the derivative of order two of I[n]; the proposed estimator can be seen in Equation (11).

$$r[\tau] = \frac{\sum_{n=0}^{N-1} \left[\frac{d^2 I[n]}{dn_2} + \left(x_I[n] - x_Q[n+\tau] \right) \right]}{\sqrt{\left[\left(\sum_{n=0}^{N-1} \left(x_I[n] \right)^2 \right) * \left(\sum_{n=0}^{N-1} \left(x_Q[n] \right)^2 \right) \right]}} \tag{11}$$

According to Saccomano et al. (2001), for the approximation of the derivative of order two, using finite differences and with the purpose of reducing the problems of instability of the derivatives of second order, he proposes for the calculation of this the application of averages on the moving averages.

The estimator is replaced in the spectral correlation density equation, as can be seen in Equation (12).

$$S_x^\alpha(f) = \sum_{\tau=-\infty}^{\infty} \left[\sum_{n=0}^{N-1} \left(\frac{\left[\frac{d^2 I[n]}{dn_2} + \left(x_I[n] - x_Q[n+\tau] \right) \right]}{\sqrt{\left[\left(\sum_{n=0}^{N-1} \left(x_I[n] \right)^2 \right) * \left(\sum_{n=0}^{N-1} \left(x_Q[n] \right)^2 \right) \right]}} \right) e^{-j\frac{2\pi}{N} n\alpha} \right] e^{-j2\pi f \tau} \tag{12}$$

5. Hardware

In order to achieve the proposed correlation estimators and spectrum sensing, the hardware architecture shown in Figure 2 was implemented.

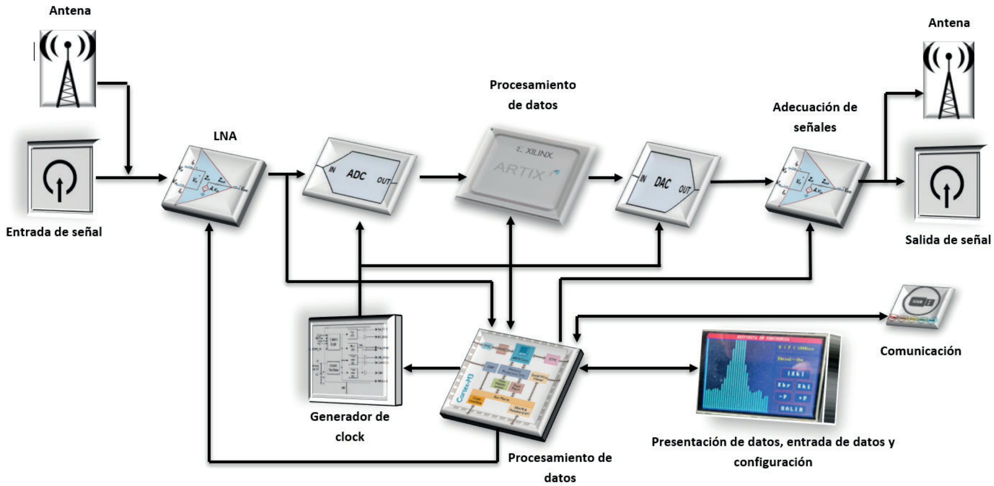

Figure 2. Hardware

The architecture allows off-line as well as real-time data processing, for which it has a microcontroller (ST Microelectronics, 2022) and an FPGA (Xilinx, 2018).

As can be seen in Figure 1, the input signal is amplified by a low-noise amplifier (LNA), which adapts the values of voltage, current, and impedance coming from the antenna to values according to the input of the digital-to-analog converter. This allows the implementation of sampling techniques in the sub-Nyquist regime; the sampling clock is generated by the clock generator block, which allows the sampling frequency to be modified.

The sampled signal is processed by the FPGA and/or by the microcontroller. These allow the implementation of the fast Fourier transform, digital filters, digital demodulation, among others.

Both, the configuration of parameters and the visualization of the signals, are processed by the data presentation, data entry, and configuration block, which has a touch screen that allows interaction with the user.

The architecture has a communication port, which allows the transmission of data for subsequent processing on a PC using dedicated software, thus implementing a third-generation SDR-like architecture.

The architecture provides for a data output for the communication and implementation of the generation of signals and modulations. This was built from a digital-to-analog converter.

6. Software

To be able to carry out the implementation of the cycle station detector, a signal digital processing system according to the third-generation systems of CR (Zhang, 2017) was designed; the system block diagram can be observed in Figure 3.

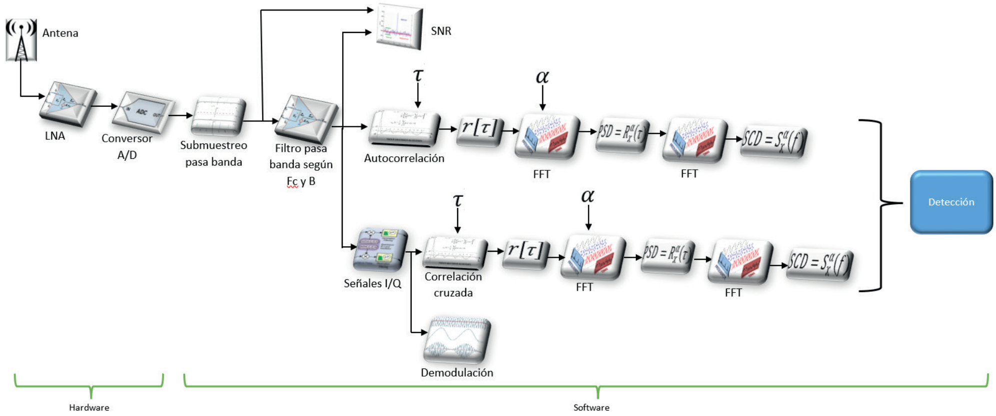

Figure 3. Blocks diagram

In Figure 3, the architecture is divided into hardware, which would consist of the low-noise amplifier, and the ad converter, whose sampling frequency is controlled by the FPGA. The sampled data is then processed by the FPGA and sent to the microcontroller for your viewing.

7. Results

For the analysis of the proposed estimators in a cyclostationary detector, this was done in two stages, one using synthetic data and the second taking real data from the spectrum.

In both cases, the response of the proposed estimators was compared with that of autocorrelation and cross-correlation.

In the case of synthetic data, a composite signal was entered into the different estimators, and the normalized spectral correlation density was calculated to be able to compare the performance of the different estimators in relation to the noise average and the signal-to-noise ratio. This can be seen in Figure 4.

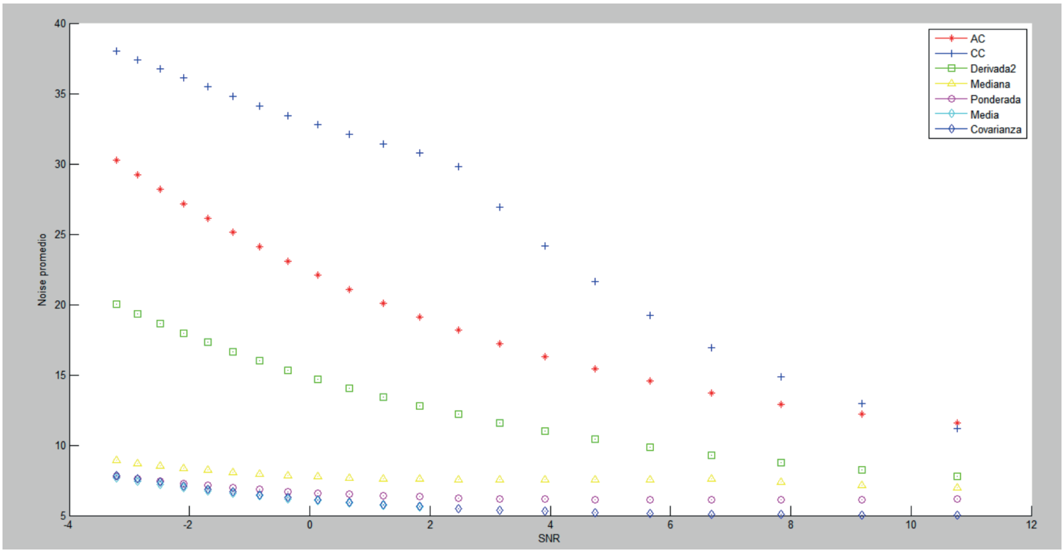

Figure 4. Noise Average vs. SNR

Figure 4 shows that the proposed estimators present better performance at low SNR than the autocorrelation and cross-correlation estimators.

However, among the estimators proposed at low SNR, the ones that present the best performance are the correlation estimator based on the mean, the sample median autocovariance, and the one based on weighting. With the increase in the signal-to-noise ratio, only the correlation estimator based on the mean and the one based on the sample median autocovariance increase their performance.

Implementing these estimators in the prototype, the results that can be seen in Figure 5 were obtained.

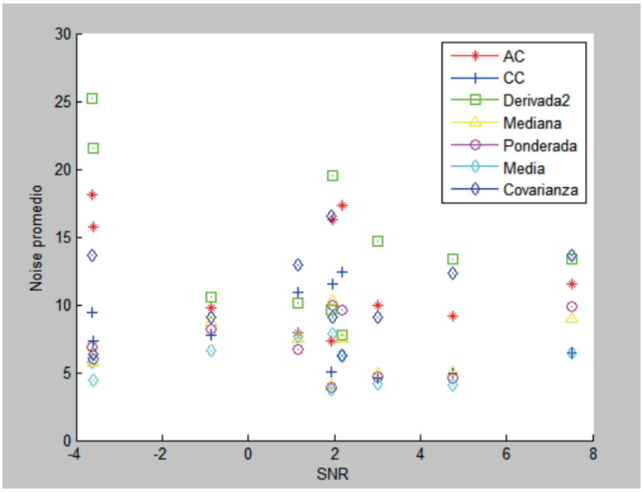

Figure 5. Results obtained from the prototype

Figure 5 shows the predominance in a low noise average of the estimators based on the mean, sample median autocovariance, and the one based on weighting in most cases. The difference that can be observed is due to the accuracy of the variables implemented in the prototype.

Regarding signal detection, the prototype was tested by injecting signals with different signal-to-noise ratios: for an 840 KHz AM-type input signal, a 10 KHz bandwidth, and a 2 KHz sinusoidal modulating signal. This can be seen in Figure 6.

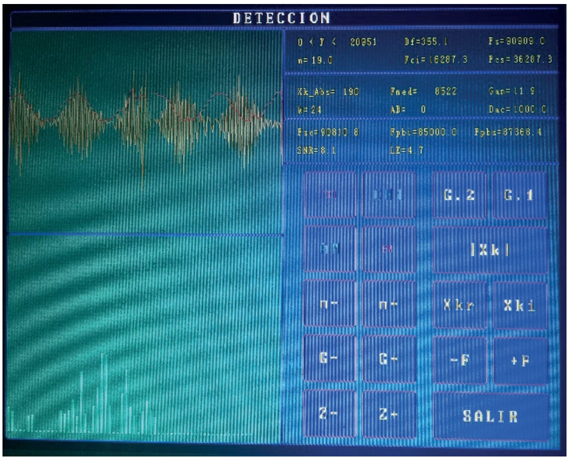

Figure 6. Spectral detection for SNR=8.1

Figure 6 shows the detection of an input signal with AM modulation, as well as its demodulation and its spectral correlation density.

Reducing the signal-to-noise ratio to SNR=6.23, the response that can be seen in Figure 7 was obtained.

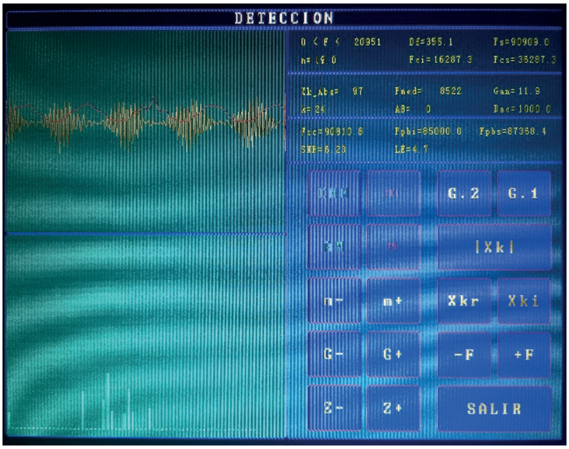

Figure 7. Spectral detection for SNR=6.23

For a signal-to-noise ratio of the order of 0 dB, the response of the equipment can be seen in Figure 8.

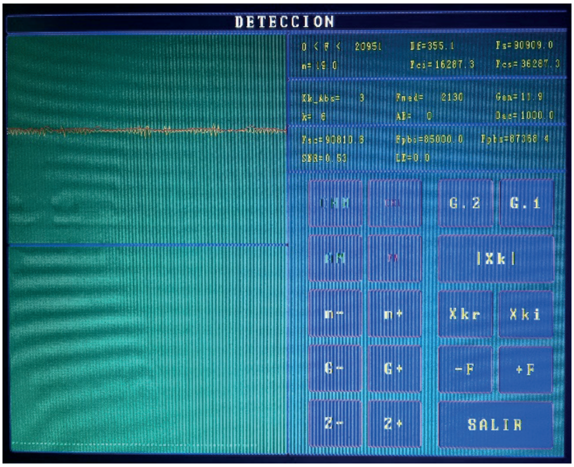

Figure 8. Spectral detection for SNR=0.53

In the Figure 8 it can be observed that the value of λ_E is zero, with which the detection is not possible to carry out. By sending the data to the PC for analysis, the spectral response that can be seen in Figure 9 was obtained.

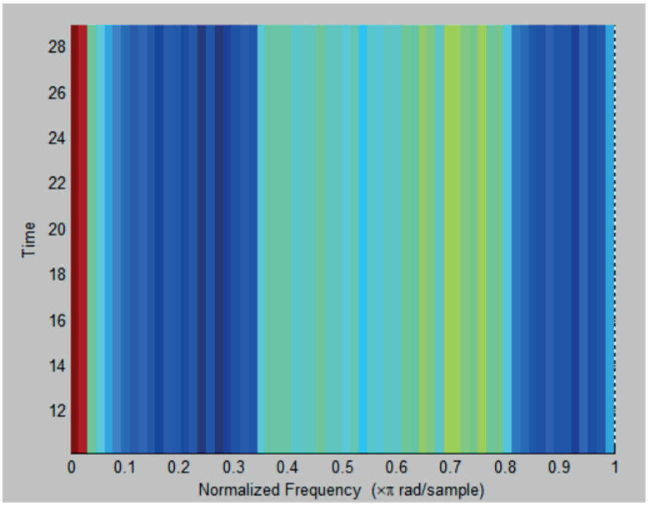

Figure 9. Spectral response

Figure 9 shows a very low power signal applying the detection algorithm and calculating the SCD scale by 1000, which can be seen in Figure 10.

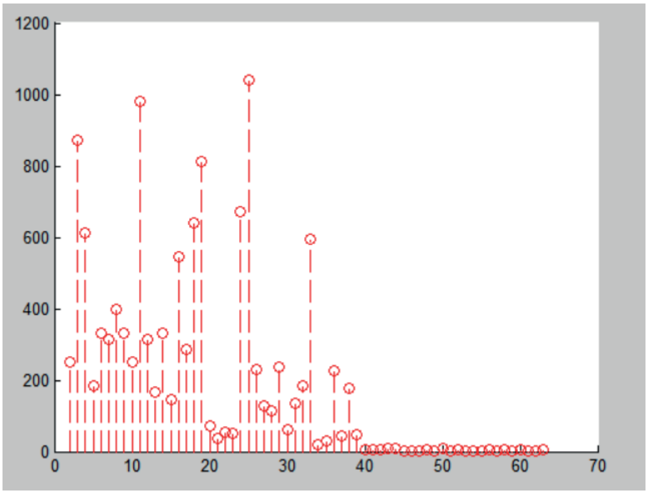

Figure 10. SCD

Figure 10 shows the response of the spectral correlation density corresponding to the input signal, but with a very low value, which would make detection unfeasible.

8. Conclusions

During the development of this work, it was observed that the proposed estimators present a better performance than those based on autocorrelation and cross-correlation at low signal-noise ratios. However, it presents a greater complexity at the time of its implementation due to the hardware and software structure proposed for the prototype. The one that best adapts is the estimator based on the weighted autocorrelation since it is the one that presents the least complexity in its implementation.

The modularity proposed for the implementation of the software allows its rapid adaptation to any estimator.

Encouraging results were obtained in screening tests performed with the weighted autocorrelation estimator.

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